Evaluation, Hybridization and Application of Quantum Inspired Evolutionary Algorithms

A brief outline of the proposed research to be carried out in pursuance
for the award of the degree of

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Area of Research

Evolutionary computation

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1.0 Introduction

Natural computing is the computational version of the process of extracting ideas from nature to develop computational systems or using natural materials (e.g., molecules) to perform computation [LN 2007].

Natural computing is divided into three main branches [LN 2007]:

- Computing inspired by nature: The main idea of this branch is to develop computational tools (algorithms) by taking inspiration from nature for the solution of complex problems.
- The simulation and emulation of nature by means of computing: A synthetic process aimed at creating patterns, forms, behaviours and organisms that (do not necessarily) resemble 'life-as-we-know-it'. Its products can be used to mimic various natural phenomena, thus increasing our understanding of nature and insights about computer models.
- Computing with natural materials: it corresponds to the use of novel natural materials to perform computation, thus constituting a true novel computing paradigm that comes to substitute or supplement the current silicon-based computers.

This research proposal reviews nature inspired computing techniques and one of its interesting variant, quantum inspired evolutionary algorithms and proposes to study quantum inspired evolutionary algorithms in detail.

2.0 Review of Nature Inspired Computing

Nature inspired computing is one of the main branches of natural computing techniques and an emerging computational paradigm for solving large scale complex and dynamic real world problems. Nature inspired computing builds on the principles of emergence, self-organization and complex systems [YZ 2010]. The main objectives of the nature inspired computing paradigm are [LN 2007]:

- Modelling of natural phenomena and their simulation in computers. The common goal in this direction is to devise theoretical model, which can be implemented in computers, faithful enough to the natural mechanisms investigated.

- Study of natural phenomena, processes and even theoretical models for the development of computational systems and algorithms capable of solving complex problems.
- To provide alternative stochastic, nature inspired search based techniques to problems that have not been (satisfactorily) resolved by traditional deterministic algorithmic techniques, such as linear, non-linear, and dynamic programming etc.

Some of the well known computational systems and algorithms evolved by natural phenomena are:

- Evolutionary algorithms inspired by Darwinian evolutionary theory
- Swarm intelligence algorithms inspired by the behaviour of groups of agents
- Artificial immune systems inspired by the natural immune system
- Social and Cultural Computing inspired by human interactions and beliefs in the society.

Evolutionary algorithms (EAs) can be termed as search based stochastic optimization algorithms developed with the inspiration of the evolution's biological processes. The main stream of algorithms developed in the EA domain are, Genetic Algorithms [GD 1989, FD 2006], Evolutionary Strategies [HG 2002], Genetic Programming [BW 1998, KJ 1999, PR 2008, KM 2010] and Evolutionary Programming [FL 1966]. In the last decade, with the emergence of quantum computing as a new computing paradigm, exploiting quantum-mechanical phenomena to perform computations, Quantum Inspired Evolutionary Algorithms [HK 2000, HK 2002] have also evolved.

Swarm intelligence can be defined as [WT 1998] "a property of a system of unintelligent agents of limited individual capabilities exhibiting collective intelligent behaviour". In general, a swarm can be considered to be a loosely structured collection of interacting agents [KJ 2001]. Based on the swarm behaviour, various algorithms have been developed to solve complex real world problems. Swarm Intelligence algorithms can also be integrated into the stream of evolutionary algorithms, as these algorithms also embody emergence and self-organization behaviour [KJ 2001]. Some of the most popular swarm intelligence based algorithms are Artificial Bee Colony Optimization [KD 2007], Particle Swarm Optimization [KJ 2001], Ant Colony Optimization [MD 1997, XH 2008] and Artificial Immune System [KJ 2001].

The Cultural Algorithm [RR 1994, RR 2008] and Society and Civilization Algorithm [RT 2003] algorithms are another set of swarm based algorithms which are inspired by the culture and the human behaviour represented by people in a society.

Although, a good number of nature inspired evolutionary algorithms exist, no one algorithm is better than the others when compared across all optimization problems. For example, the Ant Colony Optimization algorithm works efficiently on finding the minimum cost paths on a graph and data clustering. Many collective robotic systems are inspired by the collective behaviour of the ant colonies [KJ 2001]. Particle Swarm Optimization algorithm has demonstrated good performance on bench marking problems and optimal design of other natural computing techniques (neural networks). Where as, the emerging swarm intelligence based Artificial Bee Colony optimization algorithm [KD 2007] has demonstrated excellent results for numerical optimization and engineering optimization problems. The Quantum Inspired Evolutionary Algorithm has demonstrated better results than the Ant colony optimization, Simulated Annealing and few variants of particle swarm optimization (HPSO and PSOPC) for real & reactive power dispatch problems [DL 2005]. These observations are in accordance with the *No Free Lunch Theorem*, which explains that for any algorithm, any elevated performance over one class of problems is exactly paid for in performance over another class [CG 2007].

The theorem seems to suggest that it may be advantageous to combine features of two or more different algorithms to form a hybrid algorithmic technique so as to address the real world problems qualitatively. Examples of such hybridized algorithms are: Genetic Simulated Annealing Algorithm (GASAA) [WZ 2005], Hybrid Immune Algorithm that combines the benefit of Artificial Immune Algorithm and Hill Climbing local search algorithm [YA 2009], A quantum particle swarm optimizer with chaotic mutation operator [LD 2008], A hybrid algorithm of QIEA and Immune Algorithms [LY 2008], hybrid version of QIEA and PSO [WY 2007, HY 2007], and a hybridization of QEA and ABC [HB 2010]. Researchers have also integrated the concept of individual emotion and emotion with group discussions into PSO [ZC 2010], which is an interesting variant of swarm based algorithms.

In the last decade, researchers focused on improvements in the basic algorithms and application of these algorithms in various complex real world business vertical domains including engineering optimization, image processing, bioinformatics, software engineering, numerical optimization, economics, power distribution, scheduling etc.

The open problems and main challenges in this domain are [YX 2006]:

- To design, high-performance evolutionary algorithms, integrating the domain knowledge into the algorithms.
- To develop on-line evolutionary systems
- To identify the classes of problems to which, evolutionary algorithms are the most suitable approaches, and develop understanding on why and how they work or they do not work.

Many of the algorithms are built with a certain number of control parameters to drive the convergence, exploration and exploitation processes in solving the problems. Automatic tuning of parameters (or guidelines for a better choice) of an algorithm and comparing multiple algorithmic techniques and their effectiveness is also one of the key research challenges in this area of study [LN 2007, GX 2011].

This research proposal, proposes to study the behaviour of one of the nature inspired computing techniques, the quantum inspired evolutionary algorithm and its application to search based software engineering and engineering optimization domains. Along with it, this proposal also explores the possible integration of principles of social and cultural computing into swarm based intelligent techniques and quantum inspired evolutionary algorithms.

The remainder of this research proposal is organized as follows. In section 3, the review of the quantum inspired evolutionary algorithms and associated open problems are discussed and in section 4 the review of social and cultural computing algorithms are presented. In section 5, the objectives of the proposed research are outlined, followed by references.

3.0 Review of Quantum Inspired Evolutionary Algorithms

3.1 Evolutionary Algorithms

Evolutionary algorithms can be termed as search based stochastic optimization algorithms developed with the inspiration of the evolutionary biological processes such as selection, recombination and mutation.

The procedure for the general evolutionary algorithm is as follows:

Begin
t ← 0 (t represents the generation)
Initialize the population P(t)
Evaluate the population P(t) using the objective function
While (not termination-condition) do
t ← t + 1; - Increment the generation
Select pair individuals (parents) from the population P (t)
Perform reproduction among the selected parents
Perform Mutation
Generate new population P(t)
Evaluate the population P(t)
End
End

As described in the above evolutionary algorithm's procedure, in the initial generation (t=0), the population P(t) is randomly generated with 'n' individuals and the population is evaluated using the problem specific objective function. In the next generation (t = t+1), the individual solutions are selected in pairs and genetic operators like reproduction and mutation are applied to generate potential next generation solutions. The next generation population is evaluated, this way the selection, reproduction, mutation and evaluation are continued until the termination condition is satisfied. The detailed description of evolutionary computation has been presented by Fogel [FD 2006] and Back [TB 1996].

3.2 Quantum Computing

Quantum computation is a research area that is built up on the principles of quantum mechanics such as uncertainty, superposition, interference, and entanglement to process information. Quantum computers build on the principles of quantum mechanics were proposed in 1980s [PB 1980, RF 1982]. Active research since then has demonstrated that algorithms designed for quantum computers are more powerful for solving complex problems than traditional algorithms designed for digital computers. Peter Shor's factoring algorithm [PW 1994, PW1998] and Grover's database search algorithm [LK 1998] are some examples which provide excellent solutions to the complex problems like factoring and unsorted search problems [PW 1994, LK 1999].

3.3 Quantum Evolutionary Computing

The integration of quantum computing and evolutionary algorithms has resulted in three different research areas in quantum evolutionary computing, they are [GX 2011]:

- Evolutionary-designed quantum algorithms (EDQAs): this area mainly focuses on automated synthesis of new quantum algorithms using evolutionary algorithms [KJ 2005, SM 2005].
- Quantum evolutionary algorithms (QEAs): QEA's focus is to implement evolutionary algorithms in a quantum computation environment in order to take advantage of quantum computation's exponential parallelism [SL 1998, MA 2004, SD 2006, UM 2006].
- Quantum-inspired evolutionary algorithms (QIEAs): QIEAs concentrate on generating new evolutionary algorithms using the principles of quantum computing such as qubits, super position, quantum gates, standing waves [MM 1995], interference[NA 1996, ZS 2005], coherence [PW 2006], in order to solve various problems in the context of a classical computing paradigm.

3.4 Quantum Inspired Evolutionary Algorithms (QIEAs)

In 1996, Narayanan and Moore [NA 1996] solved the travelling salesman problem using a quantum inspired genetic algorithm which used quantum interference as a crossover operator. This motivated researchers to take advantage of the quantum computational parallelism and integrate it into the evolutionary framework.

Han and Kim [HK 2000, HK 2002], proposed a practical QIEA algorithm by integrating the principles of quantum computing and evolutionary algorithms.

Quantum inspired evolutionary algorithms have two main characteristics:

1. Adoption of Q-bit representation, to describe individuals of a population. Q-bit representation provides probabilistically a linear superposition of multiple states.

2. Adoption of Q-gate as the evolutionary operator, which can guide the individuals toward better solutions and to generate the individuals for the next generation.

In conventional EAs, encoding the solutions onto chromosomes uses many different representations which may be generally grouped into three classes: symbolic, binary, and numeric [HR 1999]. In quantum computing, the Q-bit is the basic computing unit. Unlike

the classical bit, the Q-bit does not represent only the value 0 or 1 but a superposition of the two.

The state of Q-bit can be given by [DC 2007]:

$$|\Psi\rangle = \alpha|0\rangle + \beta|1\rangle \qquad (1)$$

Where, $|0\rangle$ and $|1\rangle$ represents the classical bit values 0 and 1 respectively. α and β are two complex numbers. $|\alpha|^2$ and $|\beta|^2$ represents the probability measure of $|0\rangle$ and $|1\rangle$ respectively and the sum of the probability measures of $|0\rangle$ and $|1\rangle$ is such that:

$$|\alpha|^2 + |\beta|^2 = 1 \qquad (2)$$

In a system, if the Q-bit register contains 'm' Q-bits, it can represent 2^m states at the same time, where $|\alpha_i|^2 + |\beta_i|^2=1$, i= 1, 2, …,m., but when the state is measured, it collapses to a single state losing its diversity.

Once, the number of Q-bits required to encode the problem is identified and the population of solutions are encoded using the identified Q-bits for each solution. A QIEA can exploit the search space for a global solution with a small number of individuals, even with one element [HK 2002].

The step by step details of the algorithms are as follows:

Step 1 - Initialize:

Initialize the population Q_{ij}, where, i = 1, 2, ……, n, where 'n' is the size of the population and j = 1,2,…,q where, q is the number of q-bits per solution/ individual. In the initial generation (generation zero), equal values are assigned to α and β of every Q-bit, so that $|\alpha|^2 +|\beta|^2=1$.

Step 2 - Observe:

Observe all the Q-bits. In the observe step, the Q-bit is collapsed into '0' or '1' state. That is, if $|\beta i|^2 >$ rand(), then, the observed state would be '1', otherwise, the observed state would be '0', where rand() $\in$ [0, 1].

Step 3 - Evaluate:

In the Evaluate step, the fitness of each individual observed solution x_i, based on a problem specific objective function, is calculated and stored. Further, the best solution 'b' among all the solutions till the current generation and its fitness f(b) is also stored.

Step 4 – Update:

Compare each and every bit of b and x_i and determine the change in α and β corresponding to each Q-bit. Different schemes are used for determining the quantum of change [HK 2002] such as Q-gates. Han and Kim [HK 2002] apply the Hadamard gate to compute the change.

Step5: - Iterate

Repeat steps 1 through 4 until the maximum number of generations or the termination condition is met.

Han and Kim used the binary observation scheme in QIEA (step 2) to solve the combinatorial optimization problems and the performance of the algorithm was compared with CGA algorithm upon a well known knapsack problem [HK 2000]. A lot of researchers augmented the QIEA with various genetic operators to increase the performance of the algorithm.

Zhang has presented a modified QIEA algorithm in which a novel update method for Q-gates and a catastrophe operator was proposed [ZG 2006]. The population catastrophe operation is applied when the best solution is not changed over a certain number of generations. The modified QIEA was applied to select the most discriminatory feature subsets from a large number of features of radar emitter signals [ZG 2004A, ZG 2004B], Vehicle routing [GH 2006], FIR and IIR digital filter design [WX 2007] and time-frequency atom decomposition [ZG 2006].

Another variant of QIEAs integrates quantum crossover and quantum mutation to the QIEA algorithm to gain the benefit of exploitation and exploration as in the case of CGA [WW 2008, DS 2008]. Abdesslem et al. [AL 2006], Meshoul et al. [MS 2005] applied this technique to the multiple sequence alignment problem, a well-known NP-hard combinatorial optimization problem in bioinformatics.

Zhang [GX 2011] compared all the three binary encoded QIEA variants on a knapsack problem of different complexity and demonstrated the effectiveness of modified QIEA [ZG 2006] compared to other binary encoded QIEA variants. According to the recent

survey on QIEAs by Zhang [GX 2011], it is interesting to observe that, there is very little or no research has been carried out to compare these three basic variants of binary encoded QIEAs on standard numerical bench marking problems.

Han in his Ph.D. thesis [KH 2003] studied the effect of Rotation gate and the Hadamard gate as the update operator. In 2011, Shengqiu, performed the convergence analysis upon the Hadamard gate [SY 2011]. There are many other quantum gates which are, C- NOT, X-Pauli, Y-pauli, Z-Pauli, Toffoli, Fredkin, Swap and Phase shift [NA 2000]. These have not been fully explored yet to understand their effect as an update operator in QIEA.

In pursuit of better performance, researchers have attempted to integrate other nature inspired techniques with QIEA and design hybrid quantum inspired evolutionary and quantum inspired swarm intelligent algorithms. Hybridizations have considered interactions between QIEA and CGAs [WL 2005], immune algorithms [LY 2007, LY 2008], particle swarm optimization [WY 2007, HY 2007] and ant colony optimization [WL 2007]. Haibin, integrated artificial bee colony optimization with Quantum evolutionary algorithm [HB 2010, ZH 2009] and the performance of the algorithm was compared against the QEA applying on a numerical optimization problem.

Zhang [GX 2011] in his survey on QIEA lists few interesting observations while analyzing the above hybrid variants of QIEA:

- Hybrid QIEA with the principles of immune operators perform more like a special kind of local search technique which can improve the QIEA performance to a considerable degree.
- Hybrid QIEA with PSO simplifies the algorithm and produces the offspring instead of table lookups for Q-gates.
- Hybrid QIEA with CGA may be a time-consuming optimization algorithm as the integration is hierarchical. QIEA and CGA components are executed without any interaction amongst them.

It is interesting to observe that not much research has been found in the literature surveyed where enhanced variants of PSO, ACO and hybrid swarm intelligence based algorithms are integrated into QIEAs.

Zhang [ZG 2007] and Liu and Zhang [LH 2008] have also proposed a real-observation QIEA to solve global numerical optimization problems with continuous variables. Real coded QIEAs are characterized by its real observation generating real valued solutions

from the Q-bits and a modified Q-gate, which uses only one parameter for adaptively guiding the individuals toward better solutions. In contrast, in binary QIEA, the Q-gate has eight angle parameters which remain unchanged throughout the evolutionary process and have to be prescribed [GX 2011]. The real coded QIEAs are more suitable for continuous and real world problems like engineering design optimization and optimization design of digital filters, controllers and signal processing.

Quantum Inspired evolutionary algorithms and its variants have been applied to various applications including Multicast routing [XH 2009], TSP [FX 2006], neural network training [GV 2005], Knapsack problem, image segmentation, scheduling and feature extraction problems including Search based software engineering.

In Search Based Software Engineering (SBSE), the goal is to re-formulate software engineering problems as optimization problems that can then be attacked with computational search [MH 2001]. This has proved to be a widely applicable and successful approach, with applications from requirements and design [YZ 2008, OR 2010], to maintenance and testing [WF 2009, AL 2010, MH 2012]. Computational search has been exploited by all engineering disciplines, not just Software Engineering. However, the virtual character of software makes it an engineering material ideally suited to computational search [MH 2001]. Unlike other application domains, there has been relatively little work is done in applying QIEA algorithms to search based software engineering problems. Some of the problems which were addressed by QIEA researchers are next release problem [AC 2012] and test data generation [KA 2010]. Therefore, it gives a great opportunity for the researchers to apply the QIEA variants to solve complex search based software engineering problems.

4.0 Social and Cultural Computing

Simulation of cultural evolution brings more comprehensive learning and evolution than simple biological evolution. Reynolds, the inventor of Cultural algorithms argued that, "the cultural evolution enables the societies to evolve or adapt to their environments at rates that exceed that of biological evolution based on genetic inheritance only" [RR 1994].

Cultural algorithms are a class of computational models of cultural evolution that support dual inheritance, from belief space and individual interactions. This model of dual-inheritance is the key feature of Cultural Algorithms which is built on the principles of

Renfrew's THINKS model [AC 1994] and which allows for a two-way system of learning and adaptation to take place.

Reynolds developed, agent-based and multi agent based models to model the early Cultural Evolution and to explore the impact of decision-making methods and resource sharing methods on population survival [RR 2004, RR 2006]. Reynolds and his team observed that various knowledge sources like topographic knowledge, situational knowledge and the fine-grained knowledge interact at the cultural level representing the Cultural Swarm, i.e., swarming behavior [RR 2003, RR 2003A, RR 2003B]. Further, experimental results have demonstrated the existence of Cultural Swarms in a belief space, supporting the Swarm hypothesis.

T.Ray argues that "Social interactions enable individuals to adapt and improve faster than biological evolution based on genetic inheritance alone" [RT 2003]. He proposed the algorithm called Society and Civilization algorithm (SCA), in which he builds the societies and the leader of the society. The group of interacting individuals in the society collaborates with the leader and other individuals in the society to evolve. The leader will extend collaboration and communication among the leaders of other societies, in the civilization in order to improve, this may lead to migration of leaders and individuals to better performing societies. The SCA was implemented on engineering optimizations problems to demonstrate effectiveness of the algorithm.

In humans, the extra somatic arbitrary symbols that are manipulated by language are efficient means of knowledge transfer and storage. Human cognition can easily benefit from the social learning since experiences can be available from the formation of symbols, instead of from directly observing other persons [XF 2004].

Furthermore, selective social learning on success experiences enables humans to form patterns of behavior quickly by avoiding time-consuming trial-and-error [FL 1997]. This will lead to individual learning only playing a secondary role due to the ubiquity and efficiency of social learning [XF 2004]. Xiao, proposed the Social cognitive optimization (SCO) algorithm based on human cognition which works for single agent model (SAM); full sharing and partial sharing multi agent models.

Exploring the different interaction models from the social behaviors and cultural beliefs and integrating them into social computing, swarm based evolutionary algorithms and quantum inspired evolutionary algorithms is a definitely promising research area.

5.0 Proposed Research Objectives

1. To experiment and analyse the performance in general and update operators for QIEA in particular.
2. To explore the possibility of hybridizing swarm optimization and QIEA
3. To explore the possibility of integrating social behaviours and beliefs in swarm based evolutionary algorithms and QIEA.
4. To apply QIEAs to specific search based software engineering optimization problems.

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